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Integrating Text into Psychological and Education Research

Latent Variable Modeling and Applications

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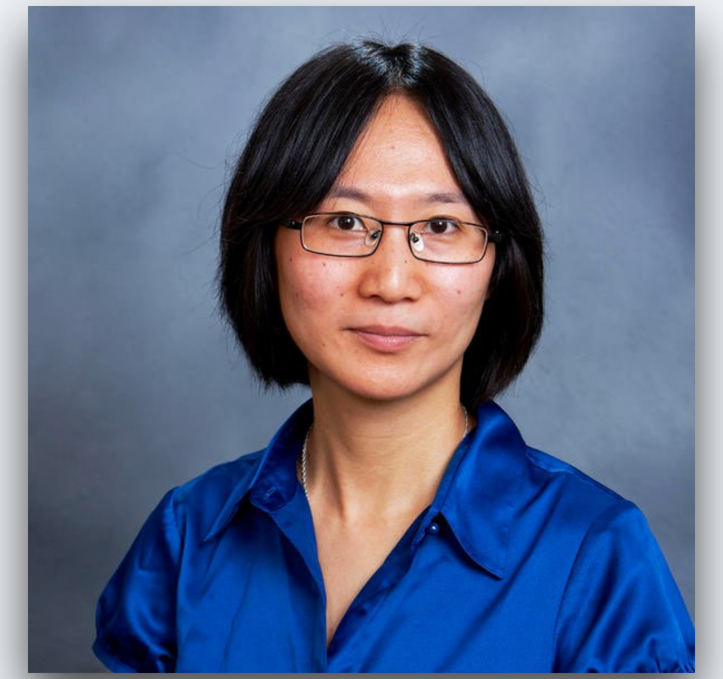
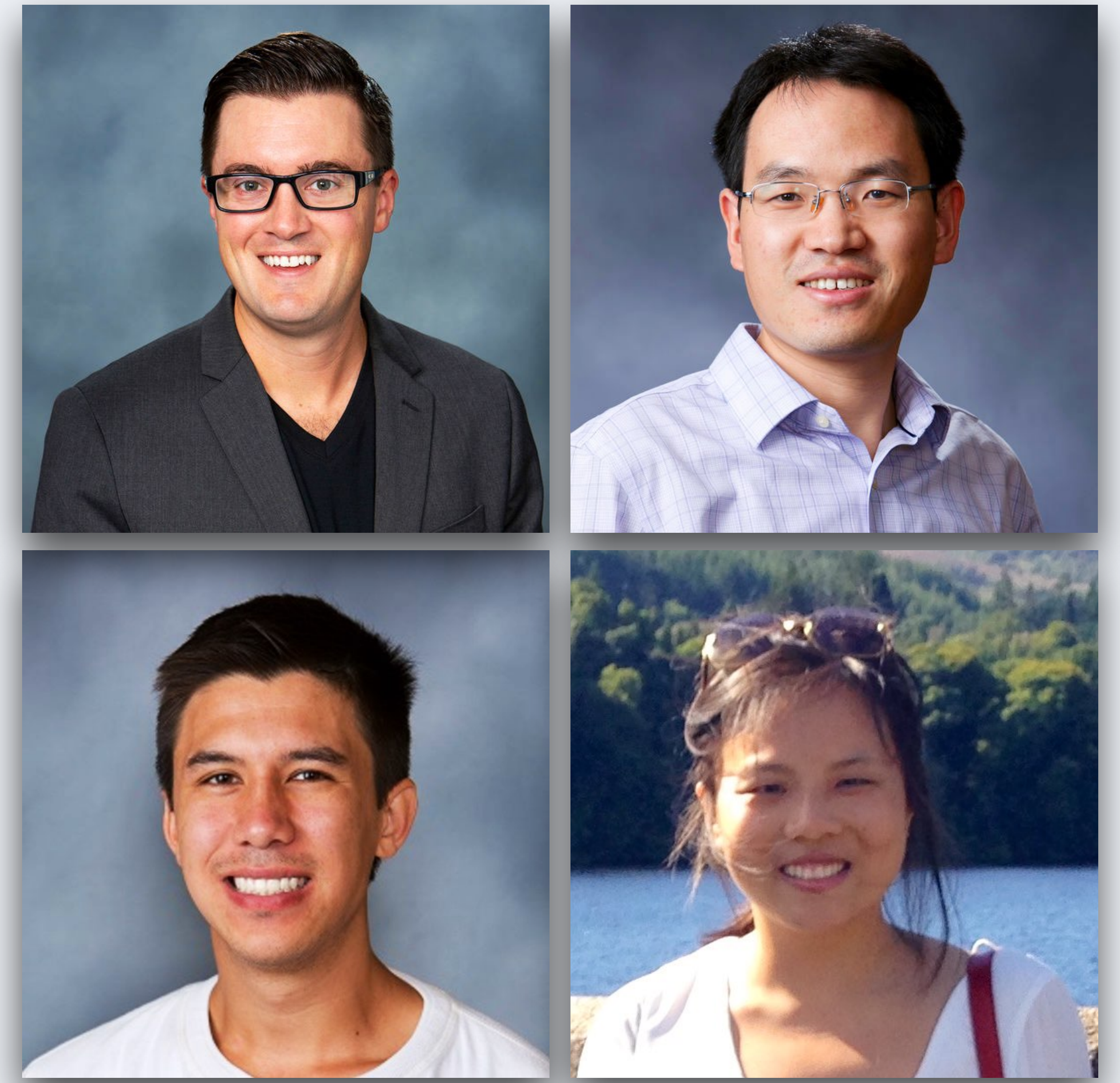
My Research

Cumulative Data Analysis



Applications

Text Mining



Outline

- Text data in psychology and education
- Dictionary methods
- Latent variable models
- A new model: supervised topic modeling with covariates
    - Estimation, interpretation, and software
    - Simulation study
    - Application to emotional dysregulation
- Future directions

Text Data in Psychology and Education

Text Data in Psychology and Education

- Long history in psychological research and educational assessment
  - Freud (1901)
  - General inquirer system (1966)
  - Linguistic Inquiry and Word Count (LIWC)
  - Topic modeling (2003)
  - Word embeddings

- Some applications
  - Measure student ability
  - Measure emotion
  - Study relationships
  - Early detection of depression
  - Identify prognostic risk factors for dementia
  - ...

(see, e.g., Bennet, 1991; Danner et al., 2001; Tausczik & Pennebaker, 2010)

But Why Not Scales?

What Are We Missing?

- Greater nuance in assessment
- Measure auxiliary or complementary information
- Closed-ended items may overemphasize testing skills, not construct domain
- Better measurement reliability
- Integration of qualitative and quantitative methods

(Boyle & Hutchinson, 2009; Ercikan et al., 1998; Jodoin, 2003; Kjell et al., 2018; Yang et al., 2018)

The Case of Two Participants

What Are We Missing?

- Data from study of nonsuicidal self-injury (NSSI) and emotional dysregulation (DERS)

- Px 1: NSSI = “yes”, Self-Rating = 7
  - DERS = 108

- Px 2: NSSI = “yes”, Self-Rating = 7
  - DERS = 63

What Are We Missing?

Interpersonal Conflict Narratives

- Px 1: NSSI = “yes”, Self-Rating = 7
  - DERS = 108
    - “Hanging out with **roommate** and **best friend**… **friend** cracked a joke that felt very insulting”

- Px 2: NSSI = “yes”, Self-Rating = 7
  - DERS = 63
    - “**Roommates** had **friends** over… they left a mess and never cleaned it in the kitchen”

Measurement: Dictionaries

Dictionary Methods

- LIWC is popular in social science research
  - Sentiment analysis
- **Predefine** constructs with lists of words

friend	joke	insulting	mess	...
2	1	1	0	...
1	0	0	1	...

Limitations of Dictionary Methods

- Inadequate scope of dictionary constructs
- Limited relevance
- Time-consuming and expensive to create
- Cannot account for polysemy

(Garten et al., 2018; Pennebaker et al., 2003)

Invariance and Polysemy

CRAWL

- Rate of movement
- Swimming stroke
- Moving on hands and knees
- “make your skin crawl”

Measurement: Latent Variable Models

Latent Semantic Indexing

(Not Really a Latent Variable Model)

- Effectively PCA for word frequencies
- Singular value decomposition of document-term matrix
- Eigenvectors and loadings interpreted as “semantic space”
- Over-fits the sample

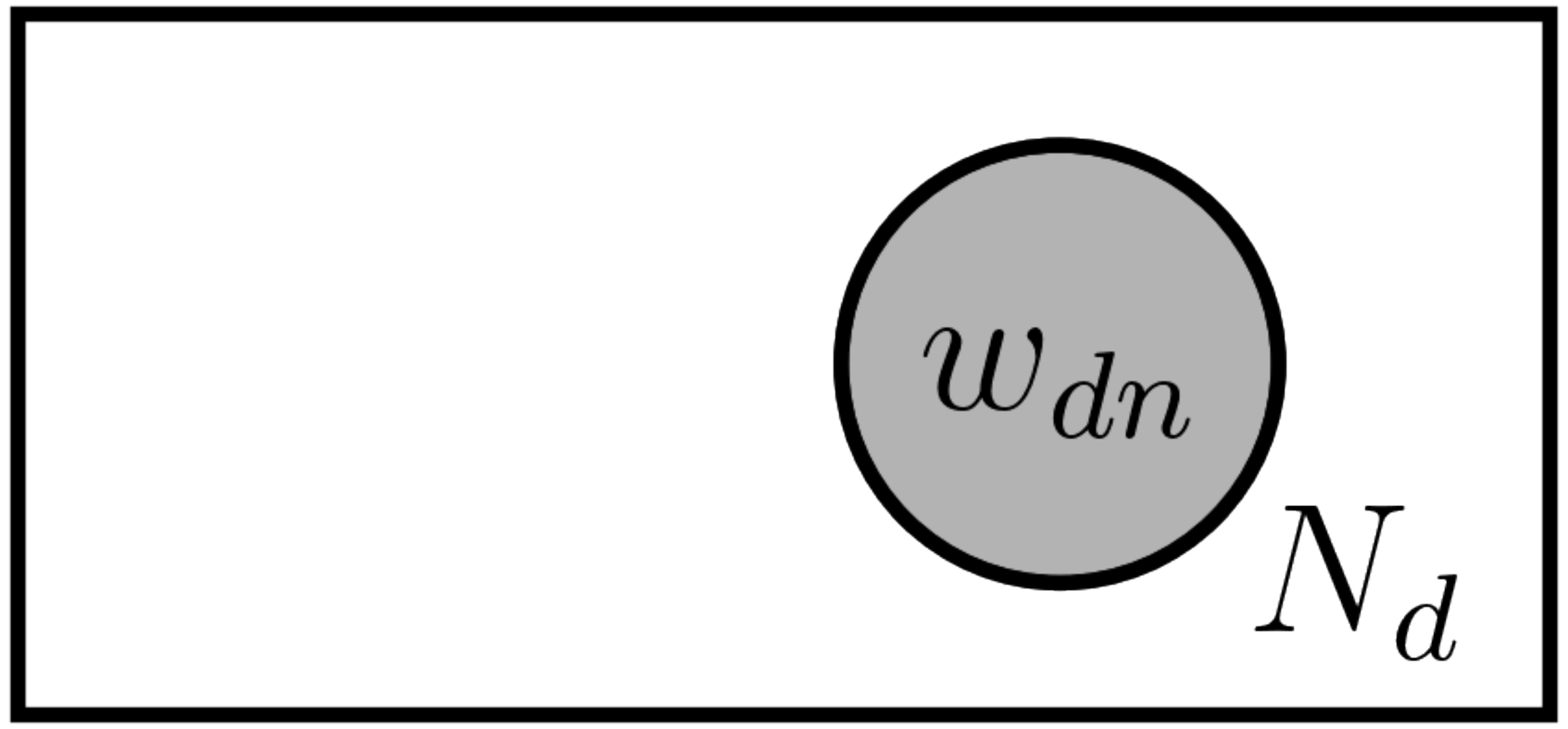
(Deerwester et al., 1990; Blei et al., 2003)

Topic Models

Latent Dirichlet Allocation

Probability distributions on words

Word w_{dn} for word 1, 2, ..., N_d



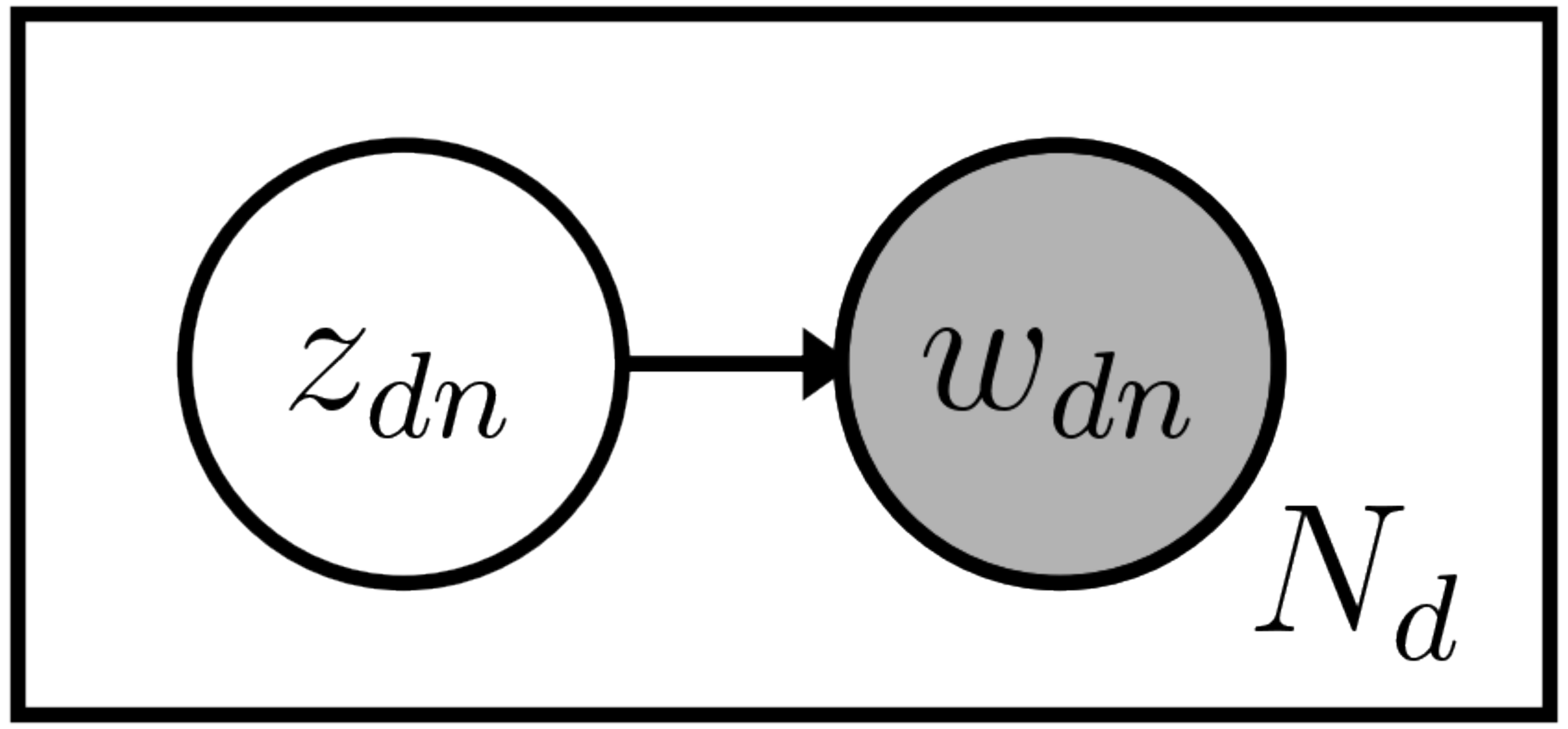
(Blei et al., 2003)

Topic Models

Latent Dirichlet Allocation

Probability distributions on words

Topic assignment z_{dn} for each word w_{dn}



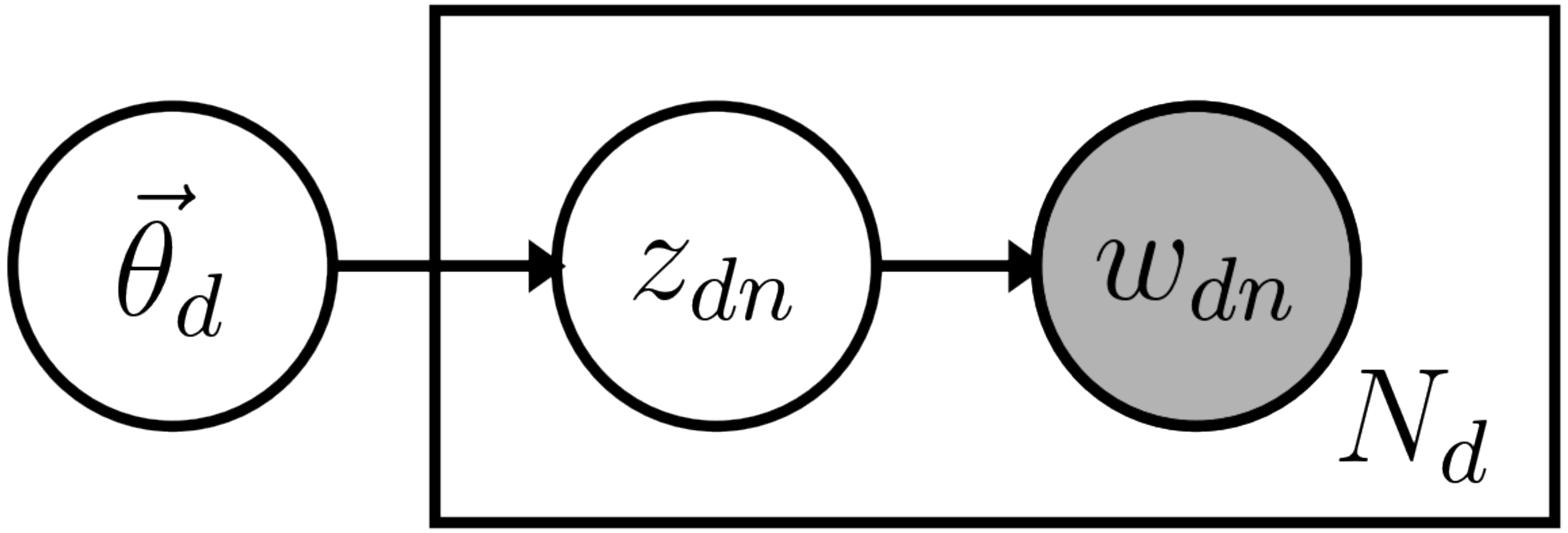
(Blei et al., 2003)

Topic Models

Latent Dirichlet Allocation

Probability distributions on words

Topic proportions $\overrightarrow{\theta}_d$ for each document



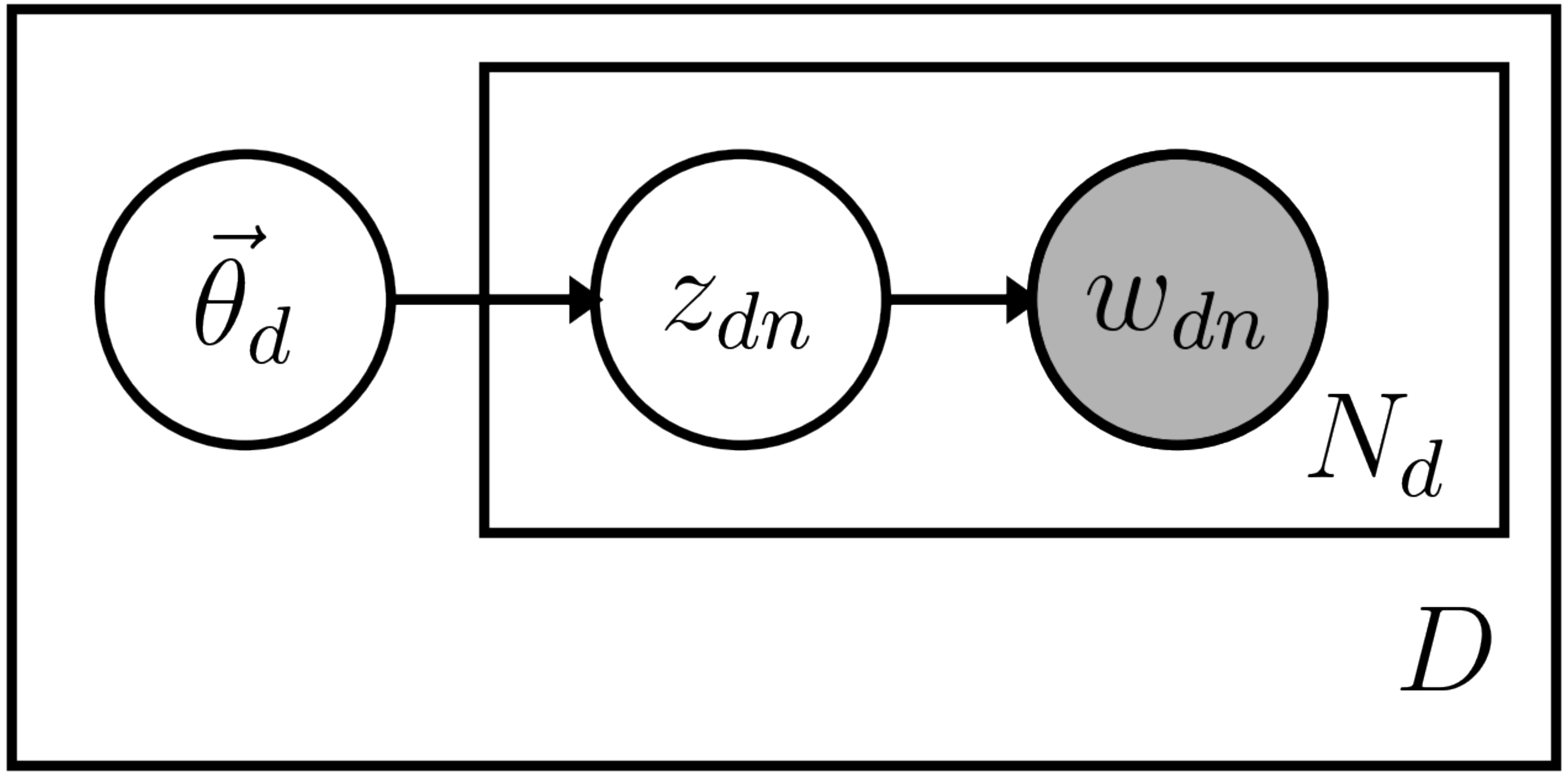
(Blei et al., 2003)

Topic Models

Latent Dirichlet Allocation

Probability distributions on words

Independent set of D documents



(Blei et al., 2003)

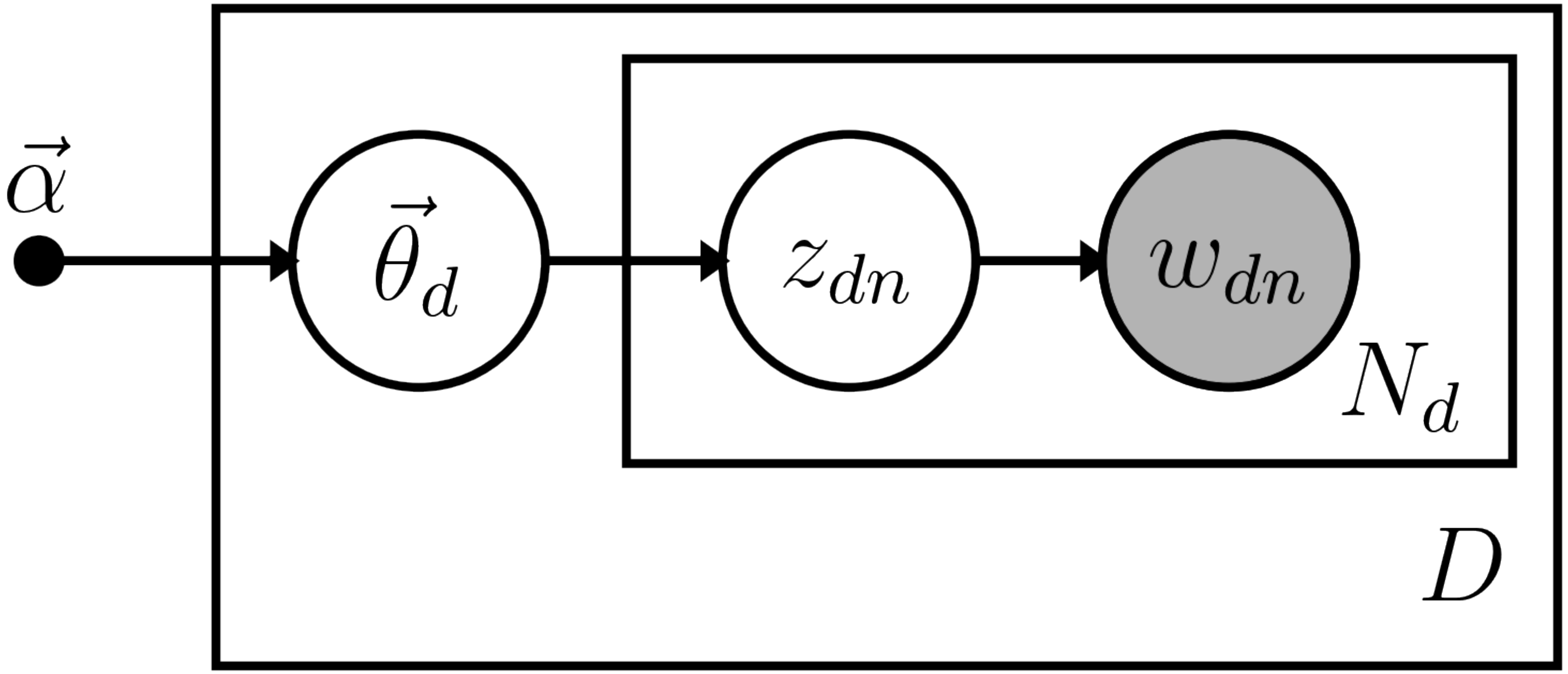
Topic Models

Latent Dirichlet Allocation

Probability distributions on words

Hyperparameter vector $\overrightarrow{\alpha}$ for topic proportions

Fixed across documents



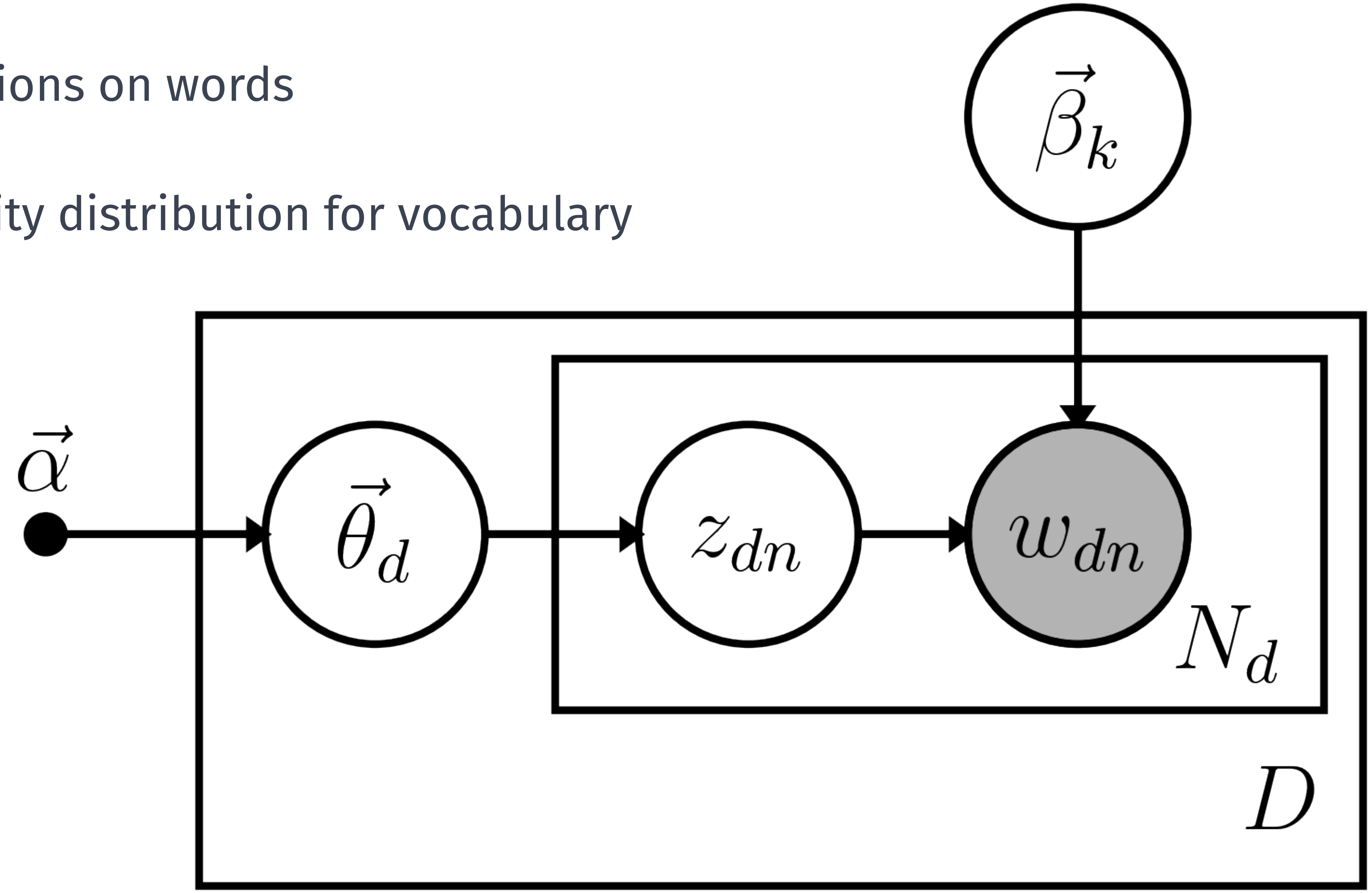
(Blei et al., 2003)

Topic Models

Latent Dirichlet Allocation

Probability distributions on words

Topic $\overrightarrow{\beta}_k$ = probability distribution for vocabulary



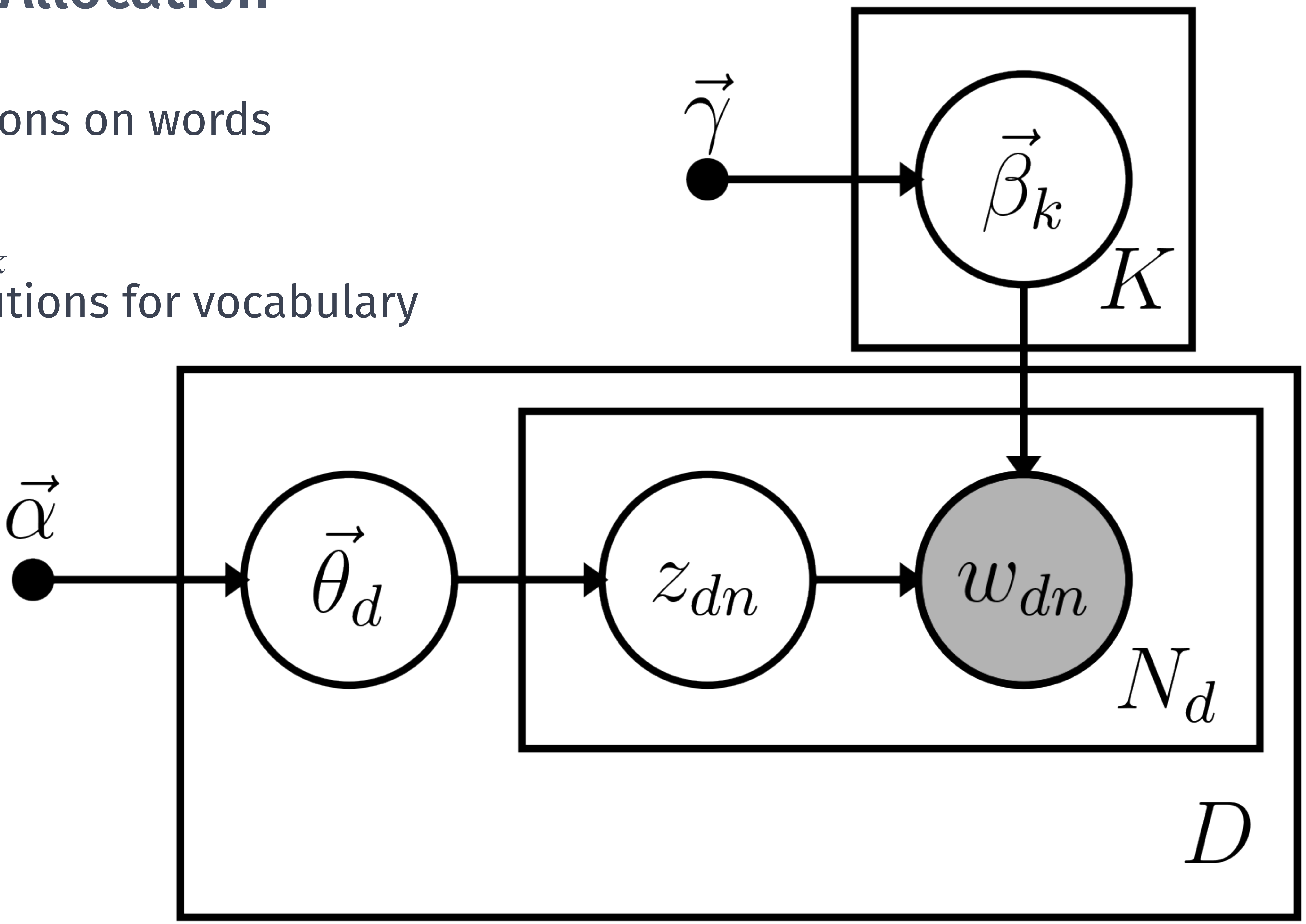
(Blei et al., 2003)

Topic Models

Latent Dirichlet Allocation

Probability distributions on words

K different **topics** $\overrightarrow{\beta}_k$
    K different distributions for vocabulary

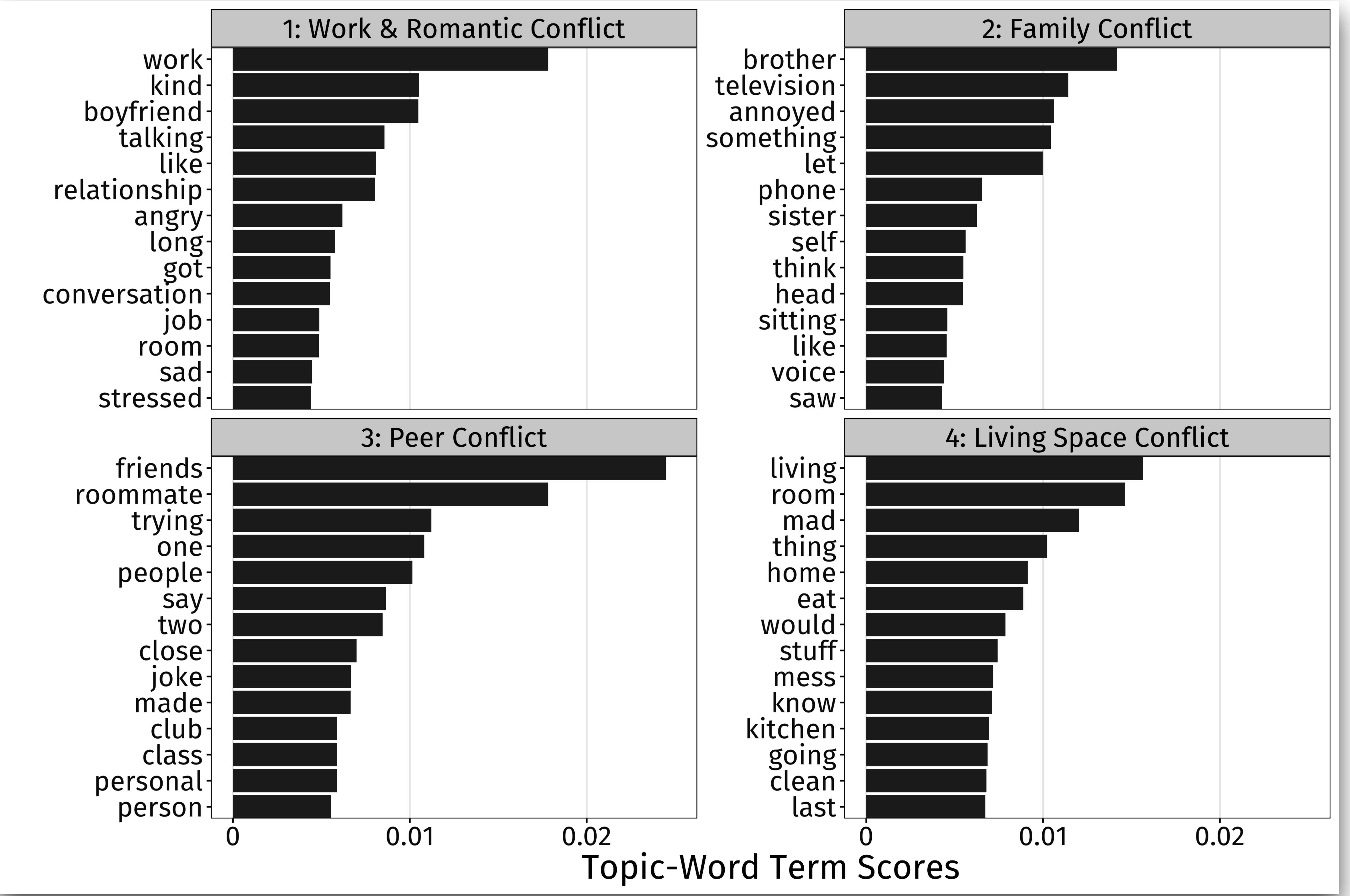


(Blei et al., 2003)

Illustration: Topics

Interpersonal Conflict Narratives

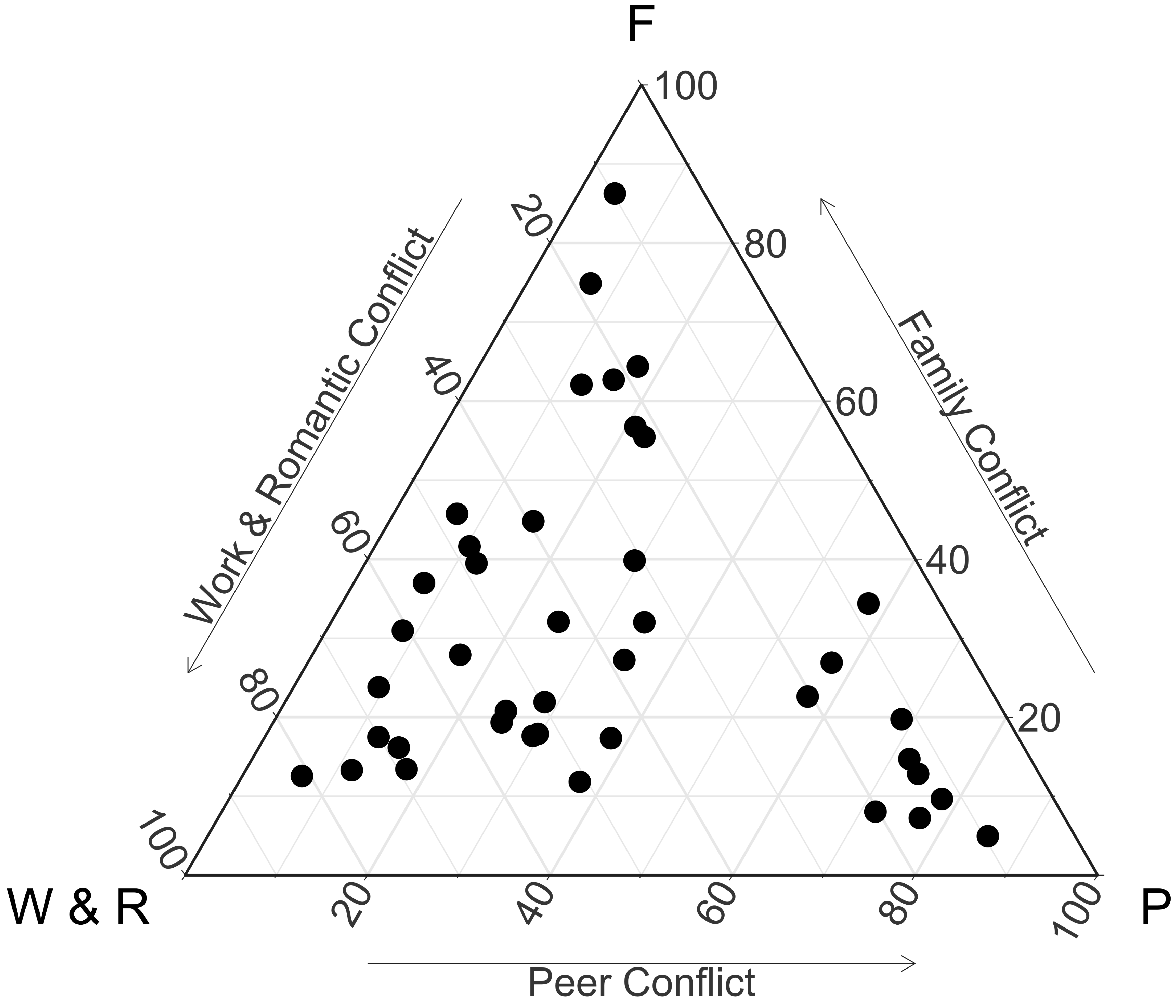
- Topic 1: Work & Romantic Conflict
  - “dad came to visit her at work… embarrassed and angry…”
  - “she and boyfriend had argument about being in a long distance relationship… she wants to move… he has to stay for his job”
- Topic 2: Family Conflict
  - “mom and dad just got a divorce… argument with mom and brother…”
- Topic 3: Peer Conflict
  - “friend made joke about her body in class… a little sad and hurt…”
- Topic 4: Living Space Conflict
  - “ex-roommate trashed the house and she was p***ed”



Wilcox, Jacobucci, Zhang, & Ammerman (under review)

Illustration: Topic Proportions

Conditioning on Living Space Conflict



Putting Topics in Context

- Like latent factors, researchers have linked topics to other measures

$Y =$  $\eta + X\beta + \epsilon$

- Surprisingly, an appropriate model is unavailable

(e.g., Finch et al, 2018; He, 2013; Kim et al., 2017; Rohrer et al., 2017)

Regression with Topics

Current Practice

- Two-stage approach
  - 1. Estimate topic proportions
  - 2. Use topic proportion **estimates** as regression predictors
- Two-stage approaches with latent variable models are problematic
- Current interpretation and inferential procedures for topics are incorrect

(Bakk, Tekle, & Vermunt, 2013; Packard et al., 2020; Petersen et al., 2012; Rohrer et al., 2017; Vermunt, 2010; Hayes & Usami, 2020)

Supervised Topic Modeling with Covariates (SLDAX)

Wilcox, Jacobucci, Zhang, & Ammerman (under review)

Funding Acknowledgement: Data presented in this talk was supported by NIMH 1F31MH107156-01A1 awarded to Brooke A. Ammerman.

Research Objectives

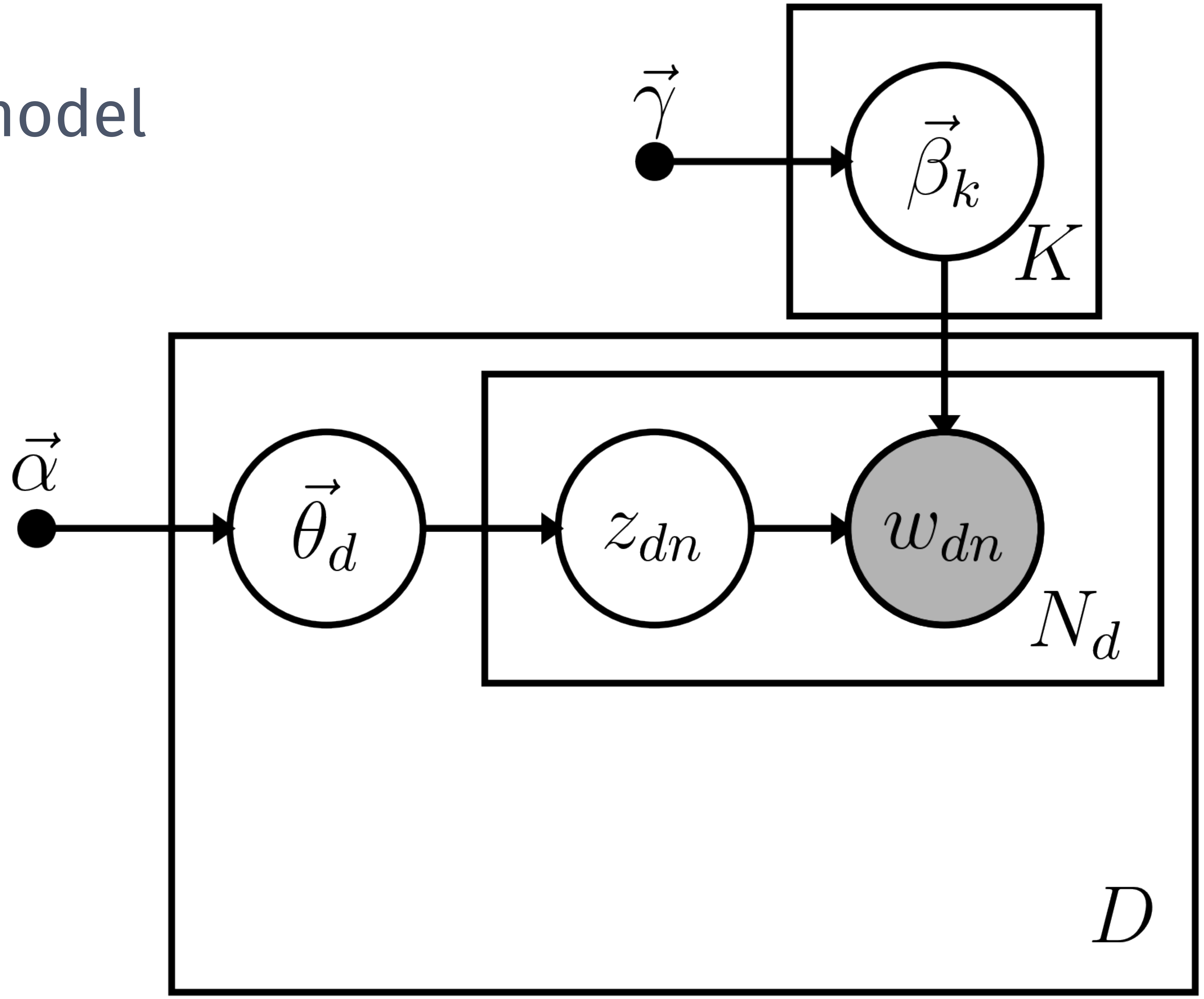
Wilcox, Jacobucci, Zhang, & Ammerman (under review)

- Develop new model to include covariates and topics to predict an outcome
- Evaluate estimation accuracy and efficiency of two-stage approach and our model
- Propose method to yield interpretable topic effects and correct inferences

Proposed Model

SLDAX — Supervised Latent Dirichlet Allocation with Covariates

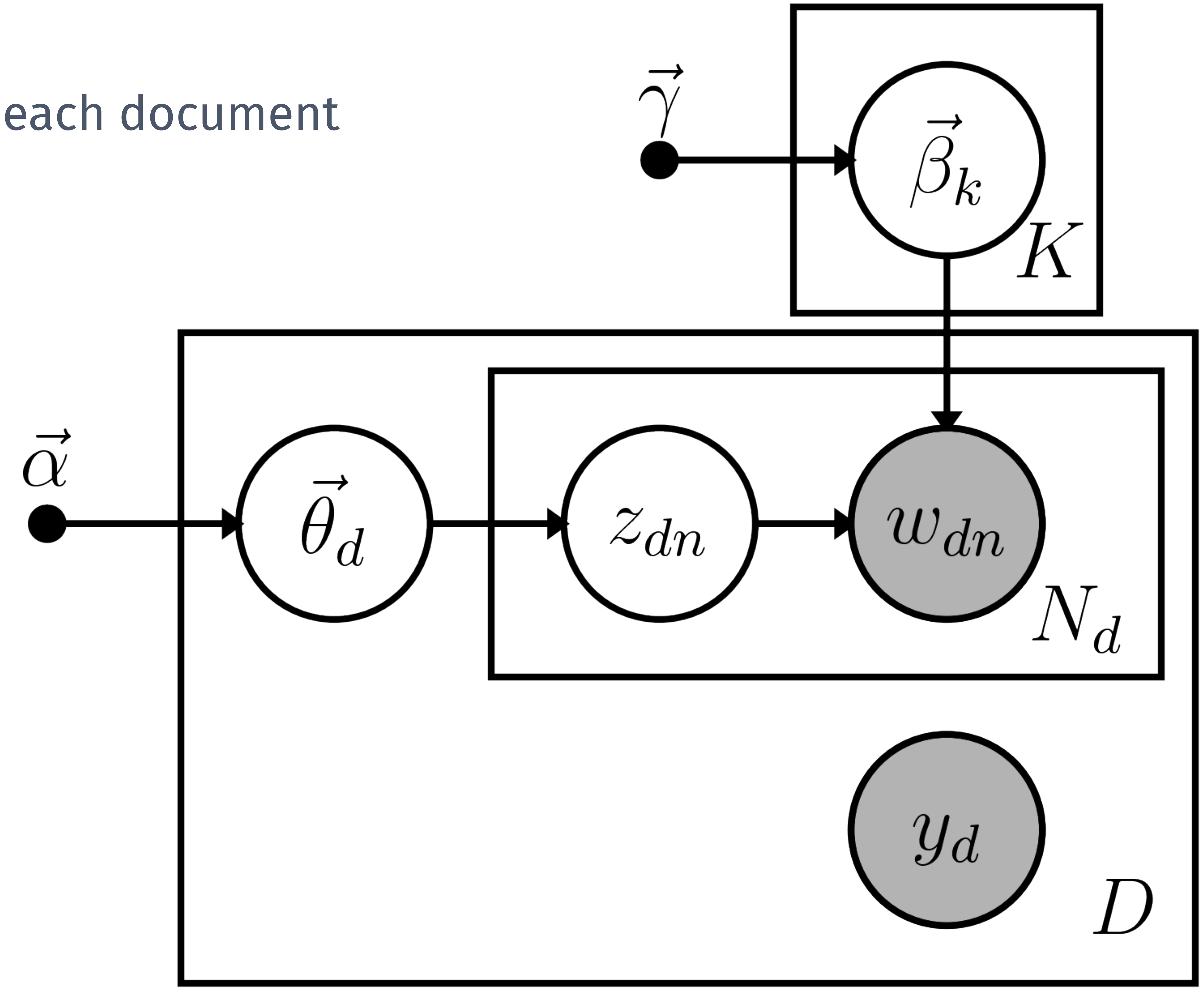
- Extend LDA model



Proposed Model

SLDAX — Supervised Latent Dirichlet Allocation with Covariates

- Outcome y_d with each document

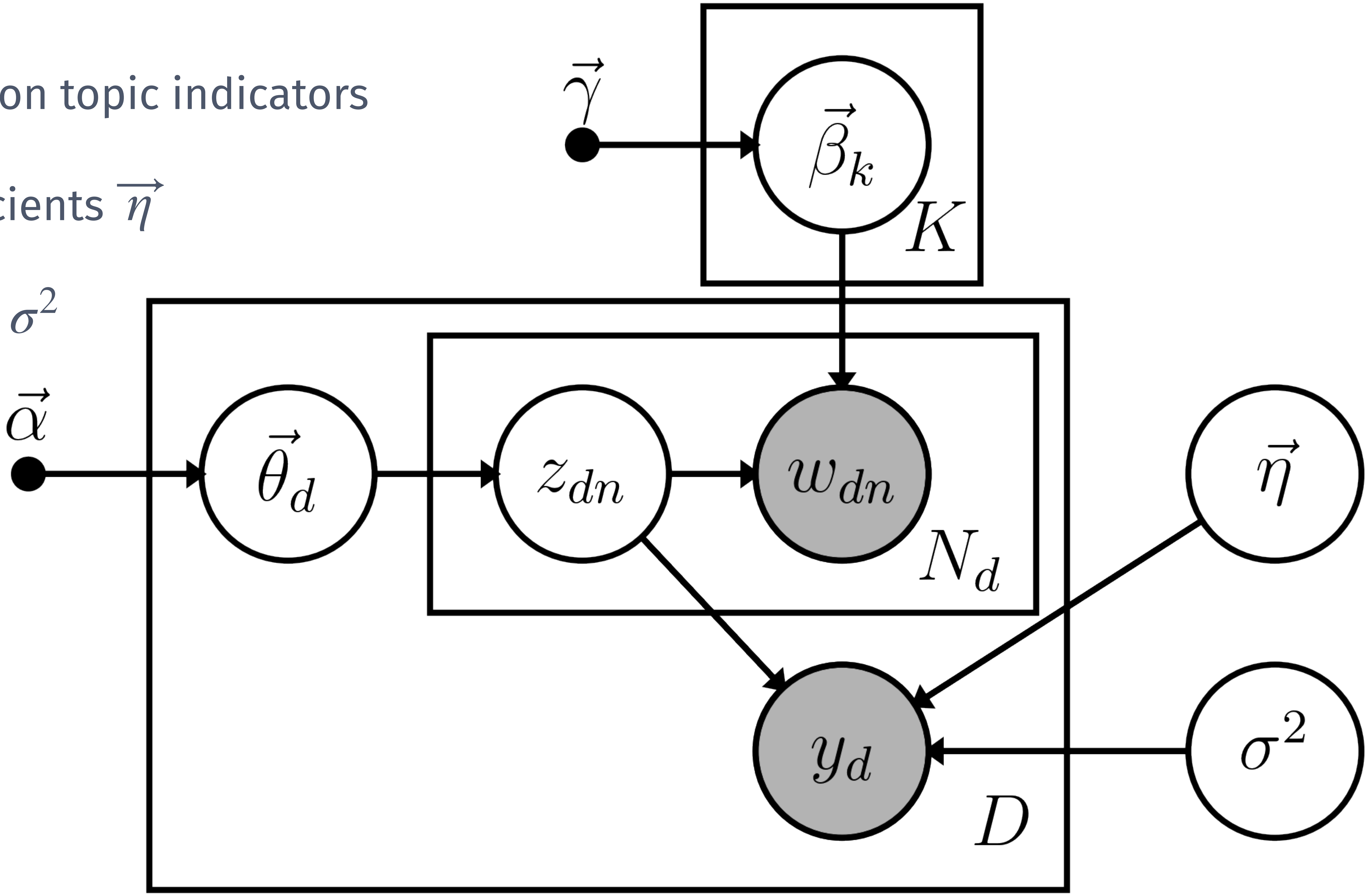


(Blei et al., 2010)

Proposed Model

SLDAX — Supervised Latent Dirichlet Allocation with Covariates

- Regress outcome on topic indicators
- Regression coefficients $\overrightarrow{\eta}$
- Residual variance σ^2

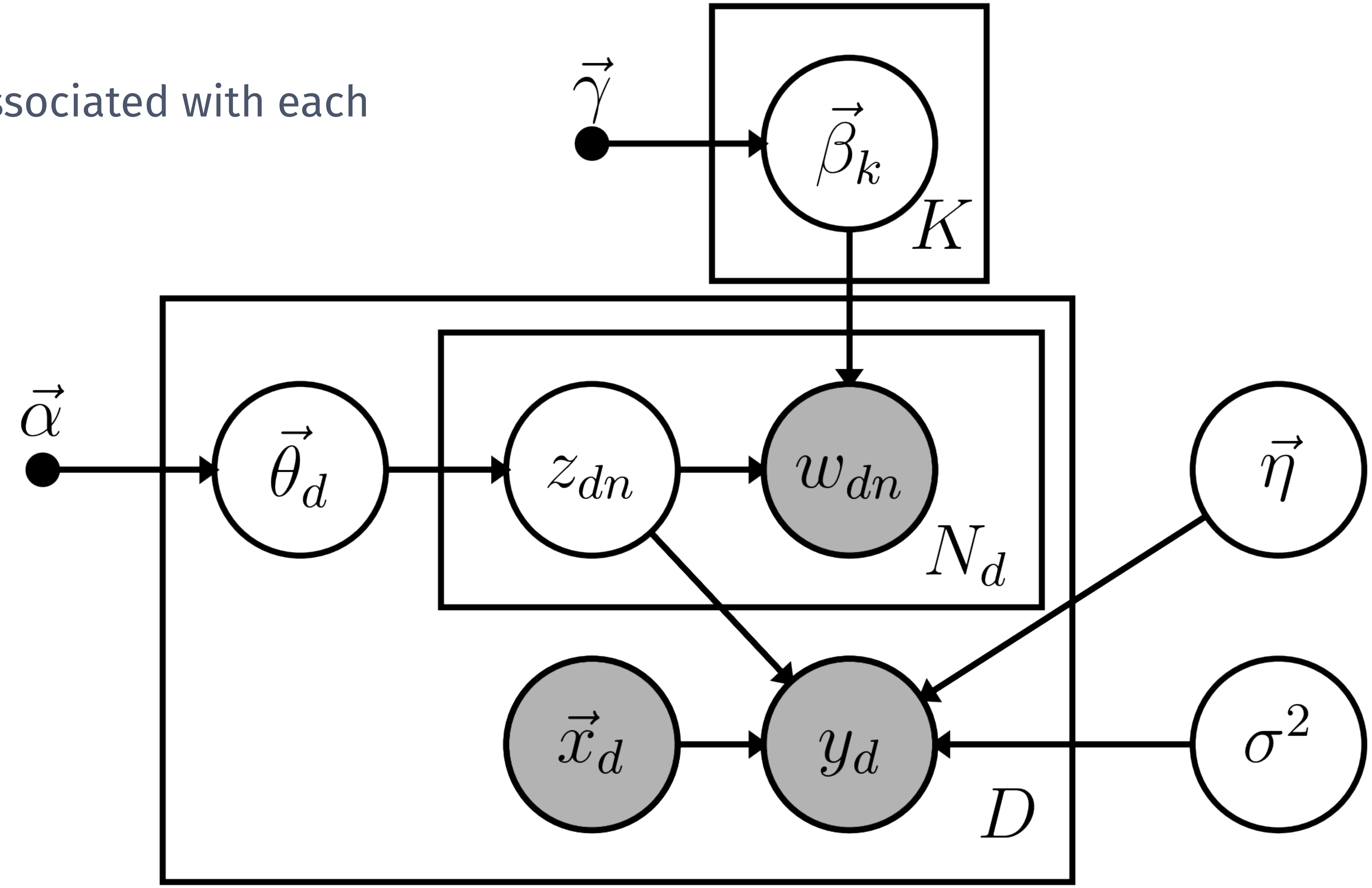


(Blei et al., 2010)

Proposed Model

SLDAX — Supervised Latent Dirichlet Allocation with Covariates

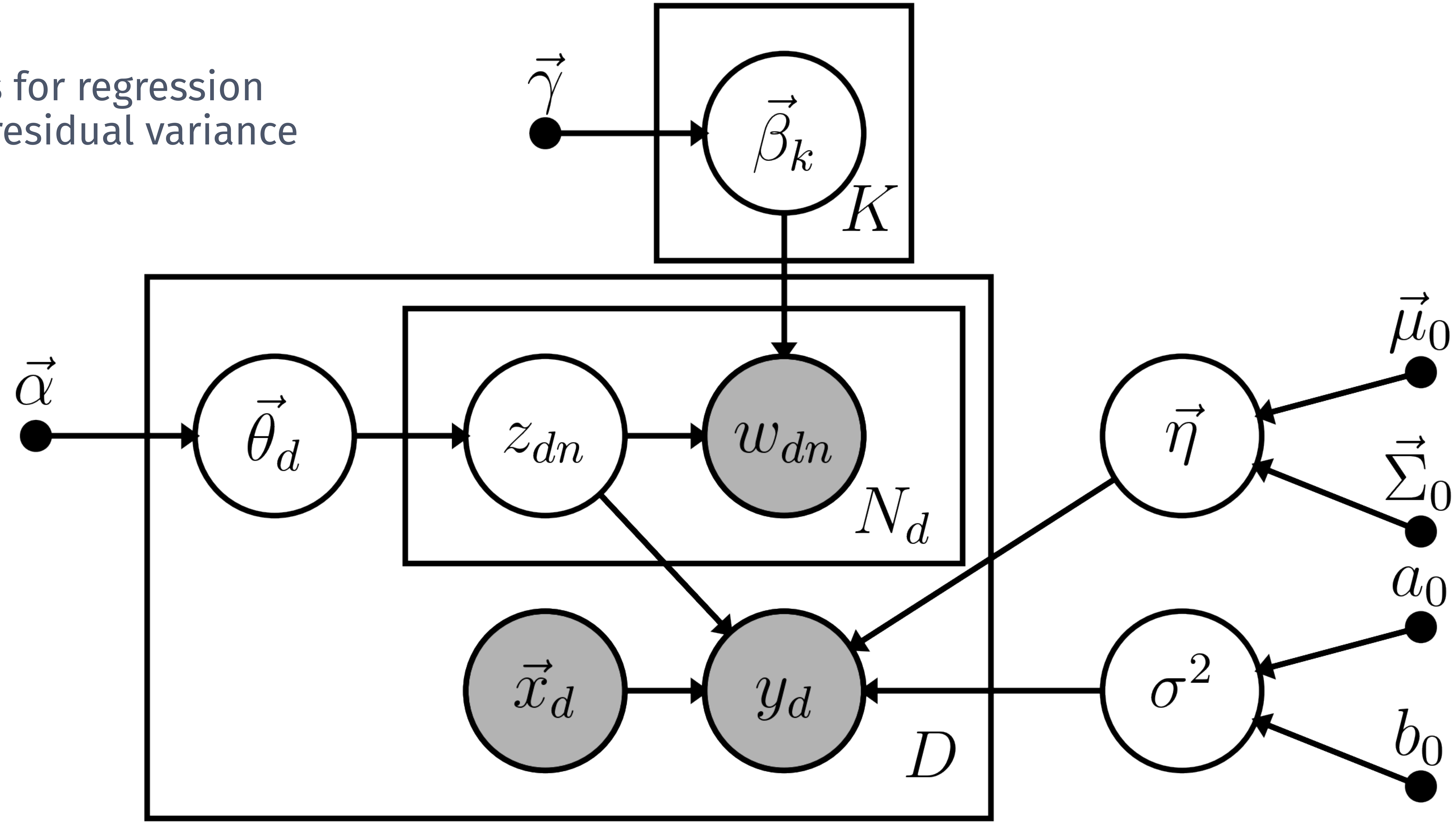
- Covariates $\vec{x}_d$ associated with each document



Proposed Model

SLDAX — Supervised Latent Dirichlet Allocation with Covariates

- Hyperparameters for regression coefficients and residual variance



SLDAX Model

$$\mathbb{E}\left[Y_d | \vec{X}_d, \vec{\bar{Z}}_d\right] = \sum_{k=1}^{K} \eta_k \bar{Z}_{dk} + \sum_{j=1}^{p} \eta_j X_{dj}$$

- Extended by generalized linear model framework to normal and dichotomous outcomes
- (Collapsed) Gibbs/Metropolis sampler for Bayesian estimation
  - Speed up mixing, reduce autocorrelation in chain
- Potential label switching handled by Stephens's algorithm

(Cassiday et al., 2020; Dias & Wedel, 2004; Liu, 1994; Stephens, 2000)

More in Paper

Wilcox, K. T., Jacobucci, R., Zhang, Z., & Ammerman, B. A. (under review). Supervised latent Dirichlet allocation with covariates: A Bayesian structural and measurement model of text and covariates. *PsyArXiv*. doi: 10.31234/osf.io/62tc3

$$L\left(\vec{\Theta}, \vec{B}, \vec{\eta}, \sigma^2\right) = \left(2\pi\sigma^2\right)^{-\frac{D}{2}} \exp\left\{-\left(2\sigma^2\right)^{-1} \sum_{d=1}^{D} \left(y_d - \vec{r}_d'\vec{\eta}\right)^2\right\} \prod_{d=1}^{D} \prod_{n=1}^{N_d} \theta_{dz_{dn}} \beta_{z_{dn} w_{dn}}$$

$$f\left(\vec{\eta}, \sigma^2, \vec{\Theta}, \vec{B}, \vec{z}_1, \ldots, \vec{z}_D | \vec{y}, \vec{X}, \vec{w}_1, \ldots, \vec{w}_D\right) = \frac{L\left(\vec{\Theta}, \vec{B}, \vec{\eta}, \sigma^2\right) f\left(\vec{\eta}\right) f\left(\sigma^2\right) \prod_{d=1}^{D} f\left(\vec{\theta}_d\right) \prod_{k=1}^{K} f\left(\vec{\beta}_k\right)}{f\left(\vec{y}, \vec{X}, \vec{w}_1, \ldots, \vec{w}_D\right)}$$

$$\vec{\eta}| \cdot \sim \mathrm{N}\left(\vec{\eta}_1, \vec{\Sigma}_1\right)$$

$$\vec{\Sigma}_1 = \left(\vec{\Sigma}_0^{-1} + \vec{R}'\vec{R}(\sigma^2)^{-1}\right)^{-1} \qquad \vec{\eta}_1 = \vec{\Sigma}_1\left(\vec{\Sigma}_0^{-1}\vec{\mu}_0 + \vec{R}'\vec{y}(\sigma^2)^{-1}\right)$$

$$\sigma^2| \cdot \sim \mathrm{IG}\left(\frac{a_0 + D}{2}, \frac{1}{2}\left[b_0 + \left(\vec{y} - \vec{R}\vec{\eta}\right)'\left(\vec{y} - \vec{R}\vec{\eta}\right)\right]\right)$$

$$f\left(z_{dn} = k|\cdot\right) \propto \exp\left\{-\frac{1}{2\sigma^2}\left(y_d - \vec{r}_d'\vec{\eta}\right)^2\right\} \times \frac{\left(n_{w_{dn}k}^{(-dn)} + \gamma\right)\left(n_{dk}^{(-dn)} + \alpha\right)}{n_k^{(-dn)} + V\gamma}$$

Software

R Package

- `psychtm`
  - In development
  - Estimation for topics models (LDA, supervised LDA, SLDAX)
  - Written in C++ for speed
- Available on Github

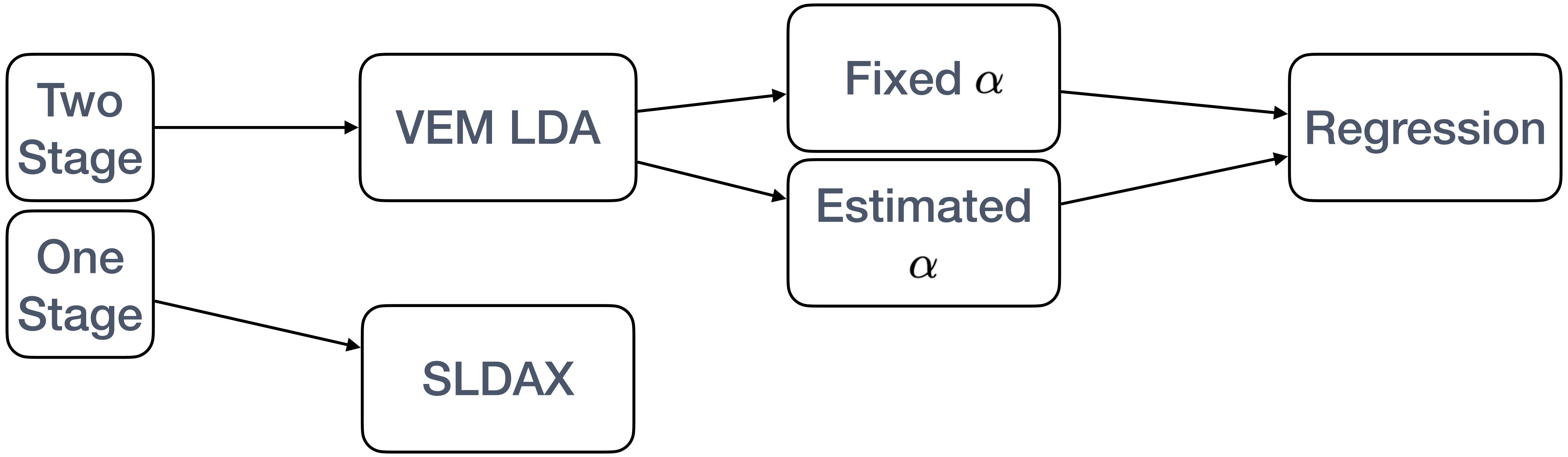
```
devtools::install_github("ktw5691/psychtm")

fit <- gibbs_sldax(y ~ x1 + x2, data = xy, docs = docs, K = 2, V = nvocab)
```

Simulation Study

Design and Methods

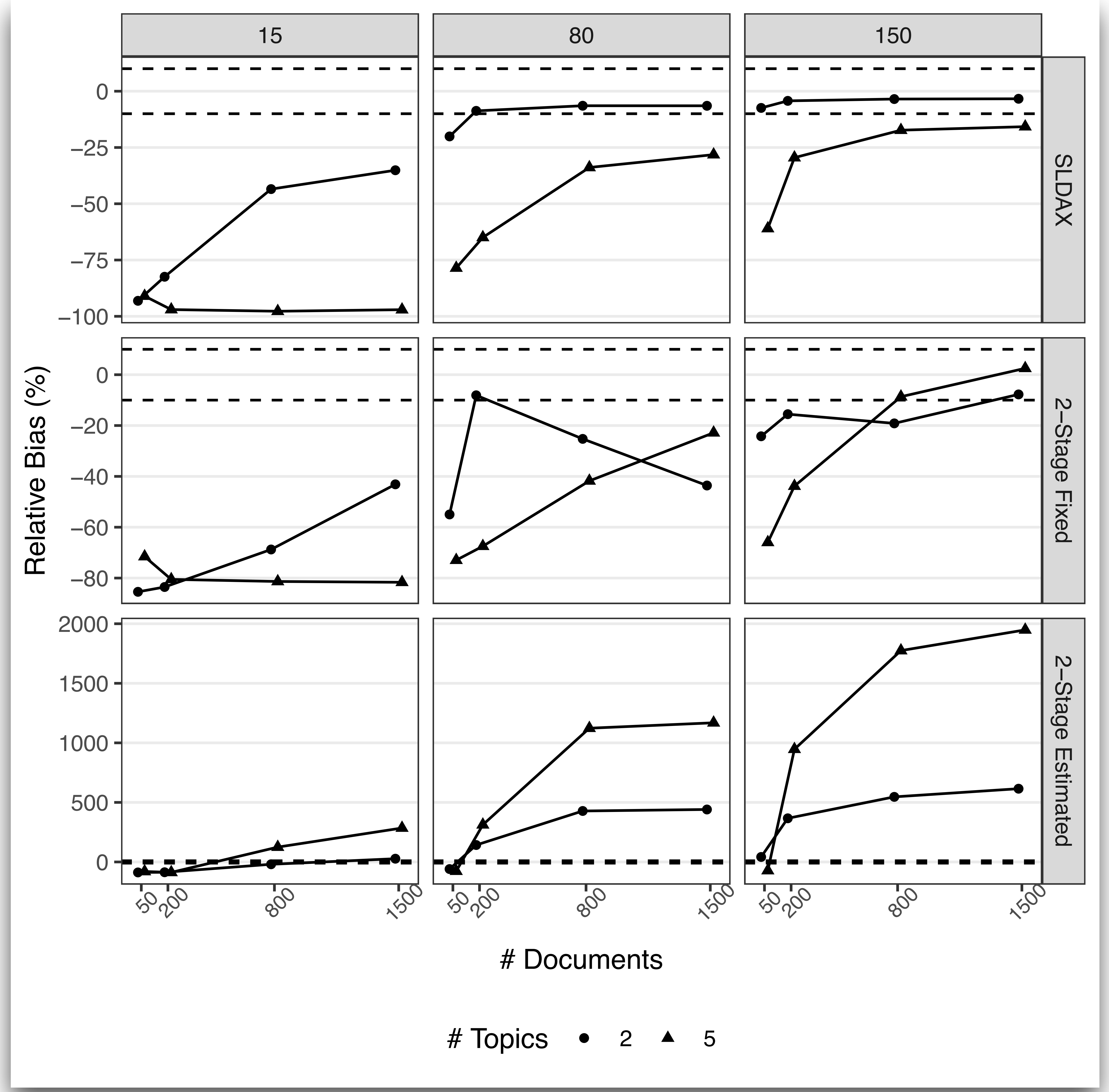
- Key Conditions
  - # topics: {2, 5}
  - # subjects: {50, 200, 800, 1500}
  - Average document length: {15, 80, 150}
- Methods



Simulation Results

Two-Stage vs. SLDAX

- Two-stage method
  - **Overestimated** regression coefficients w/ estimated hyperparameter
    - This gets worse with more data!
  - Inconsistent (?) w/ fixed hyperparameter
- SLDAX estimates less biased
  - Require adequate sample size and document lengths
  - Can be underestimated
  - More efficient (smaller MSE) — not shown here



Interpretation & Inference

Topic Regression Coefficients

- Topic proportions are ipsative (i.e., sum to 1)
- Corresponding regression coefficients are conditional means of the outcome when **only** that topic is present
  - Common to see all positive or all negative coefficients
  - Meaning depends on conditional mean of outcome
  - Generally, cannot compare them to 0

Interpretation & Inference

Contrasts

- Define the "effect" of a topic on the outcome with contrasts, e.g.,

$$c_k = \eta_k - \frac{\sum_{k' \neq k}^{K} \eta_{k'}}{K-1} \stackrel{?}{=} 0$$

- Sample c_k from posterior distribution
- We can interpret the sign and credible interval w.r.t. 0
- Better weighting using Piepel's method

(Park, 1978; Piepel, 1982; Snee et al., 1976)

Empirical Application

Relationships Among Nonsuicidal Self-Injury and Interpersonal Stress

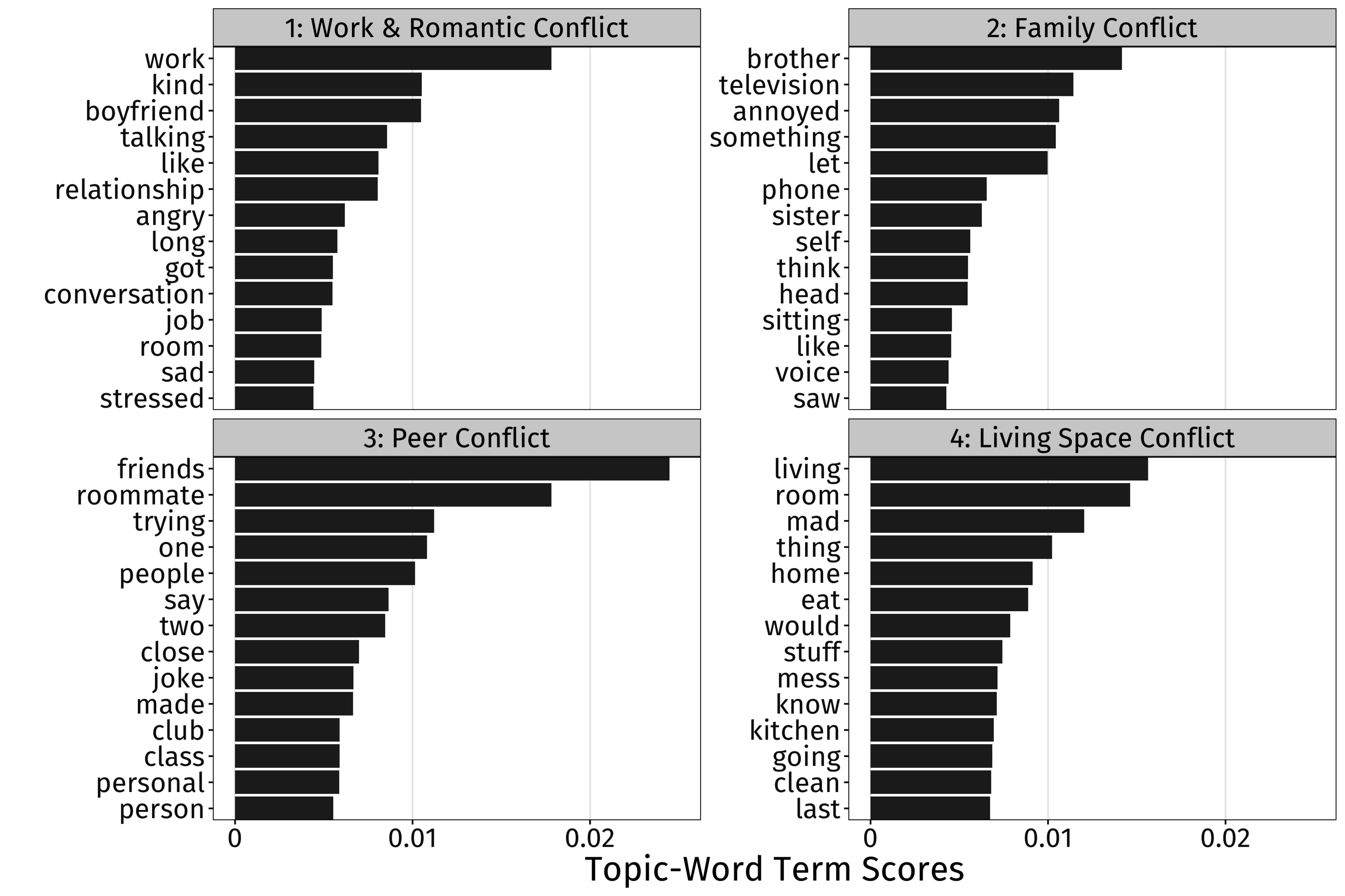
- Undergraduate sample (n = 41); majority (84%) identified as female
- 56% reported NSSI history
- Interview transcripts about a recent upsetting interpersonal interaction
  - After pre-processing, median word count = 63
- Self rating of degree of upset/distress for the interaction (Likert: 1—10)
- Modeled **emotional dysregulation (DERS)** with
  - NSSI history
  - Self rating
  - Interpersonal interaction narrative transcripts

(Gratz et al., 2011)

Empirical Application

Topics Measured by Interpersonal Interaction Interviews

- Topic 1: Work & Romantic Conflict
  - “dad came to visit her at work... embarrassed and angry...”
  - “she and boyfriend had argument about being in a long distance relationship... she wants to move... he has to stay for his job”
- Topic 2: Family Conflict
  - “mom and dad just got a divorce... argument with mom and brother...”
- Topic 3: Peer Conflict
  - “friend made joke about her body in class... a little sad and hurt...”
- Topic 4: Living Space Conflict
  - “ex-roommate trashed the house and she was p***ed”



Empirical Application

SLDAX Regression Results

- NSSI history associated with greater DERS
- Topics from negative interpersonal interaction jointly explain significant variability in DERS, $\Delta R^2 = 15\%$
  - NSSI and self rating explain 24%
  - Topic effects likely attenuated

	Coefficient / Contrast (SE)	95% BCI
Self Rating	0.7 (2.2)	[-3.7, 5.0]
NSSI History	21.7 (6.5)	[8.8, 34.4]
T1: Romantic & Work Conflict	92.3 (10.42) 9.7 (12.3)	[71.4, 112.6] [-15.1, 33.7]
T2: Family Conflict	67.0 (11.9) -20.4 (13.3)	[43.2, 90.7] [-46.3, 6.4]
T3: Peer Conflict	101.0 (10.3) 19.5 (11.6)	[80.7, 121.8] [-3.5, 42.3]
T4: Living Space Conflict	75.4 (11.5) -10.8 (13.1)	[52.1, 97.8] [-36.8, 14.9]

Summary

- Developed new model to incorporate topic model for text into regression framework
- Proposed model yields more accurate and efficient estimates than two-stage approach used in standard practice
- Document length is key for improving regression estimates
- Number of documents/subjects is key for power
- Contrasts are needed for interpretation and inference
- Text can measure what available scales may not

Future Directions

- Integrate topic model and IRT model for closed-ended and constructed response items (Hong & Wilcox, in preparation)
- Longitudinal topic modeling
    - Topic measurement invariance
- Exploratory vs. confirmatory topics and validation

Questions?

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Wilcox, K. T., Jacobucci, R., Zhang, Z., & Ammerman, B. A. (under review). Supervised latent Dirichlet allocation with covariates: A Bayesian structural and measurement model of text and covariates. *PsyArXiv*. doi: 10.31234/osf.io/62tc3